Marketing Bulletin, 1999, 10, 11-23, Article 2

Capturing Images in a Net: Perceptual Modelling of Product Descriptors using Sorting Data

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One task facing market researchers is that of profiling a product, by taking a predefined list of descriptors and eliciting the relationship between the product and each descriptor in turn ("applicable" or "not applicable"; "good description" or "bad description"). Accuracy is gained if in addition the relationships among the descriptors are known: they become a meaningful nomological net, which can be depicted as a geometrical model. In this study, a large, extensive net is constructed, using an innovative split-deck sorting procedure to collect the data. It is argued that in comparison with the conventional treatment of sorting data, the custom-designed algorithms involved in the construction of this net are less susceptible to artefacts.

Keywords: perceptual modelling, sorting, product descriptors

Introduction

A common goal of market researchers is to investigate the 'image' of a product, i.e. the collection of attributes which consumers and potential consumers associate with it. Such research is often a precursor to *changing* its image – creating new associations in the minds of the public. If there is little to distinguish the product from competing brands, then the only way that its producer can gain an advantage over the competitors is through manipulating such images, for example, by linking an alcoholic beverage with a sense of excitement, or prestige; or an appliance with a sense of reliability. It may be desirable to reposition a product on the market, shifting the segment of consumers to whom it appeals, if it is presently competing too closely against alternative brands within a restricted niche. Or it may be that the product is a potential one, yet to be released, and the objective is to compare the images created by alternative advertising strategies.

In any case, such an investigation of image might proceed by taking a large set of descriptors – a lexicon of words (or phrases) which could be used to describe the product (what Stephenson 1980, termed a concourse) and using them to build up a profile of the product. Participants can be presented with the lexicon, and asked to pick out those words which describe the product. Alternatively, participants might be asked to list those words which come to mind when they think of the product, with those ones which are not part of the lexicon being subsequently ignored. The resulting frequencies of word usage indicate the 'strength of association' between the product and each descriptor in turn.

A useful preliminary step, however, is to display the relationships between the descriptors themselves, in the form of either a spatial model or a tree structure, and this is the focus of this paper. A spatial model is a sort of 'semantic space' (Osgood 1971), representing each descriptor by a point, with the distances between points corresponding to the dissimilarities perceived between descriptors: words with similar meanings are represented by points in close proximity. In contrast, a tree model (De Soete & Carroll 1996) seeks the same correspondence, but the distances are not spatial ones: they are measured along the links in a tree-like network consisting of nodes and links connecting them. Some of the nodes, corresponding to “leaves”, represent the descriptors while the remainder are points where links or “branches” join.

The feature of both spatial and tree models which makes them into useful tools is that the product itself can also be located within them, as an additional point (Carroll 1972). The general principle is that the strength of the association between the product and the *i*-th descriptor should be (inversely) related to the distance between the corresponding points. These we may label as x_p and x_i, while d_{ip} indicates the distance between them. In the spatial model, the subset of descriptors which consumers associate with the product form a ‘cloud’ in the semantic space, centred on x_p. This is referred to as the Ideal Point model (Carroll 1972), where x_p, representing the product, is the “ideal point”. Analogous techniques exist to incorporate products within a tree model – though in this case, the concept of ‘centrality’ is not applicable (De Soete, DeSarbo, Furnas & Carroll 1984).

Once locations in either model have been obtained for a number of different products, it becomes clear which brands the product of interest is competing with most directly, and whether there are niches or market segments as yet untapped. From this point of view, the question of relocating a product becomes one of shifting x_p to a new position, x_p'.

Of course these descriptor models are not essential for calculating and interpreting product profiles. But models have the advantage that they reduce the description of the product to a small number of parameters (the co-ordinates of x_p, in the spatial case). A prescription for modifying the product’s image is stated concisely, in the form of desired changes to those parameters, rather than as a new value for each separate descriptor. Note also that raw measurements of descriptor/product association are independent of one another, and are thus subject to ‘noise’ or statistical fluctuations which can only be reduced by increasing the number of participants in a study. The d_{ip} that are derived from an entire profile of such associations, by compressing them into the framework of a spatial model or a tree, are mutually dependent, and may be less noisy. In this respect the model can act as a noise filter.

The emphasis of the present paper is on the procedures of data collection and analysis required to construct models for large item sets, in this case an 88-word lexicon. The ‘semantic space’ needs to be sufficiently fine-meshed to capture the intermediate shades of meaning which arise when informants list all the product-associated words they can think of, and sufficiently general to encompass their reactions to a variety of products. For comparison, studies of personality description typically find it necessary to map 100 or more words, to encompass the range of words, and the subtle distinctions among them, which informants use to describe the personalities of themselves or others (e.g. Slooff & van der Kloot 1985; Goldberg 1992). It is quite likely that a lexicon of similar size would be required for market applications.

This paper reports an extension of the Method of Sorting, which we term GPA-sorting (for Group-, Partition-, Additive-sorting). Its purpose is to elicit from subjects as much information as possible about the dissimilarities they perceive between the descriptors, easily and reliably, in a relatively short time. The normal Method of Sorting itself (Weller & Romney 1988; Coxon 1999) is a convenient and familiar procedure for dealing with large item sets. Among many other applications it has been used in ethnology, to map how a culture’s concepts or constructs are interrelated, and in psychology, to map personality descriptors. There is some overlap between lists of personality descriptors and the product-descriptive words introduced below.

A number of methods are available for constructing spatial models from the (dis)similarity data, such as Homogeneity Analysis or Multiple Correspondence Analysis (Slooff & van der Kloot 1985). However, we have found that these produce cruder spatial maps, distorted by artefacts. In particular, any tendency of the items to fall into clusters seems to be exaggerated. Artefacts also appear with the conventional MDS approach of pre-processing sorting data to produce estimated dissimilarity values based on "co-occurrences”. Growing dissatisfaction with the flaws of the co-occurrence treatment has led to several alternative analyses for sorting data being proposed (e.g. Daws 1996).

In this study, data collected using the GPA-sorting procedure were converted into a spatial model by applying an iterative technique, the Method of Reconstructed Dyads, directly to the subjects’ sorting decisions (see Bimler & Kirkland 1997, 1998). The same direct approach also works for constructing tree models. The results are displayed both as a spatial map and as a hierarchical "tree", and to check for artefacts, the results produced using the Method of Reconstructed Dyads are compared with those produced by a conventional MDS analysis of the same data.

Method

Procedure

Eighty-eight adjectives were selected from Callebaut, Janssens, Lorre & Hendrickx (1994) and printed on slips of card to facilitate sorting. The words are quite metaphorical ones, equally applicable to many different products, since they are intended to capture the *image* rather than the objective qualities of a product. One can imagine them as describing the characteristic consumer, or the life-style of that consumer. Thus the list of words has much in common with lexicons used in studies of personality, and of implicit personality theories (e.g. Slooff & van der Kloot 1985).

Fifty-four participants were recruited from staff and students at Massey University, and used the GPA procedure to sort the 88 adjectives.

In the GPA-sorting procedure, the informant’s task comprises three phases. Two are shared with the method of G/A-sorting, described elsewhere (Bimler & Kirkland 1998). For these two phases, the participant begins by sorting the items into groups, placing similar items together. This Group (G-) phase is followed by an Additive (A-) phase in which the participant is asked to choose the most similar pair of groups, and to merge them, repeating this process as often as possible. The successive merging may stop when all the items are amassed in a single pile, or when the collective level of dissimilarity among the remaining piles is such that no “most similar pair” can be singled out.

But two refinements have been added to allow for a large number of items. A ‘split-deck’ design was used, to reduce the difficulties involved in positioning 88 items on a table-top at once, without overlapping, and attending to them all concurrently while arranging them into groups of ‘similar meaning’. This approach consists of shuffling the deck of cards, and dividing it into (approximate) halves – or even into thirds in some cases – to be sorted separately. A different random division was created for each subject.

Second, a Partition (P-) task was introduced before the Additive phase, having the opposite function, in that participants were invited to increase rather than decrease the number of groups. They did this by considering the groups they had created in the initial Group stage, and asking themselves if any of those groups were not completely homogenous; i.e. if they could be further divided into subgroups. For instance, a group of 4 words might be partitioned as a tight cluster of three near-synonyms, plus one outlier. These subdivisions (if any) were written down as part of that subject's data. Following this, the subject restored the groups of words initially created, and proceeded with the Additive phase. For similar extensions of the Method of Sorting, see Boster (1986), Stefflre *et al* (1971).

Some individuals sorted a single split-deck while others proceeded to a second or third. In total, GPA-sorts were collected for 96 of these split-decks. Additionally, individuals described the arrangement of the items in varying amounts of detail, since they did not all proceed with the same number of merging steps in the Additive phase (the record being eight merges: some participants skipped the A-phase altogether). In the analyses, different merging stages are interpreted as revealing different levels of structure in the model. The solutions are naturally weighted towards those informants who contributed most data, but this is not seen as a major problem: it is more a case of some informants filling more of the gaps left by others.

Analysis

The result of GPA-sorting, from each participant, is *a sequence* of arrangements of the descriptors into groups, as if the participant has sorted them into pigeonholes on the basis of similarity, sorting them repeatedly with the number of pigeonholes varying. There is a grouping from the G-phase, of course, but the P-phase yields another arrangement with more groups, while each successive merging step from the A-phase yields another one, with fewer groups. So a given grouping in the data set might have come from a G-, P-, or A-phase, but in the analyses they are all treated on an equal footing.

A spatial model was obtained from these data, a process known as Multidimensional Scaling (MDS). This model is a compromise between the different ways in which participants demarcate groups, an attempt to reconcile their disagreements. The 'Method of Reconstructed Dyads' (Bimler & Kirkland 1997) was the MDS algorithm used. In this, the emphasis is on the sequence of groupings, which each participant has provided, in order of decreasing number of groups. Since each transition from one grouping to the next consists of choosing particular groups to combine, the transitions are treated in terms of merging decisions. The decisions are in effect comparisons between similarities: by merging two groups, the participant informs us that they are perceived as more similar than all the pairs, which were *not* merged at that stage. This is explicit for the sequence of groupings comprising the A-phase, but the transition between P- and G-phase groupings is interpreted in the same way, as is the transition between the trivial arrangement in which the items are initially presented, with each one as a group by itself, and the P-phase grouping. These decisions are summed over participants, and a model is designed which agrees with them as much as possible.

The Method of Reconstructed Dyads reduces these decisions about *group* similarities to comparisons between the similarities of *items*. If a group is constructed (at any stage) containing only two items, a dyad, this indicates that the informant perceives the similarity between those two to be greater than all the similarities between pairs of items in *different* groups. The model should reflect this judgement. For larger groups, the interpretation in terms of comparisons is more difficult, since it no longer follows that all items in large groups are relatively similar. For instance, items A and B may co-occur because both are similar to C, a third item in the group, rather than with each other. In general, though, it should be possible to reconstruct a *chain* of dyads connecting A and B, only using items from the group they belong to, such that the similarity for each link in the chain is relatively high. This procedure is described in more detail elsewhere (Bimler & Kirkland 1997, 1998). The program implementing it, MASSORT, is available from the authors.

In order to compare the results of the Method of Reconstructed Dyads with a conventional MDS analysis, "co-occurrences" were derived from the groups and treated as estimates of the inter-item similarities. The co-occurrence of two items is simply the proportion of the total number of arrangements (summed over participants and over each participants' sequence), in which they belong to the same group. Since the split-deck design means that many arrangements will omit one or other items for any given pair, only split-decks in which both are present are summed to give this "total number of arrangements" on which this proportion is based. The underlying idea is that if the pair members have similar meanings, they will be grouped together frequently. Conversely, if the items are dissimilar then they should be grouped together in few of the participants' G-phase groupings, co-occurring only late or not at all in their A-phase sequences, leading to a low average co-occurrence.

An alternative way of summarising similarity data is to construct a dendrogram, or tree, rather than a spatial 'map'. The construction of a tree model proceeds in an analogous way to the spatial case. A series of adjustments are made to progressively increase its goodness-of-fit with the sequences of similarity comparisons extracted from informants' sorting data.

Results

MASSORT produced the spatial model shown as Figure 1. We chose a three-dimensional solution, and rotated it to emphasise the axes shown as D1, D2, D3. There is an element of taste in the choice of alignment and of axes, since spatial models can be rotated without affecting their goodness-of-fit. D1 ranged from words like *dominant*, *aggressive*, *powerful* at one extreme, to *kind*, *caring*, *generous* at the other. D2 ranged from *active*, *vital*, *energetic* to *pensive*, *obedient*, *reserved* and *passive*. D3 ranged from *stylish*, *expensive*, *elegant*, *chic* to *solid*, *firm*, *simple*, *safe*. The dimensions are continua, rather than dichotomies, an important feature of this type of analysis. Though there are local concentrations of adjectives, the gaps between them are not empty. For example, between the clusters *active* / *energetic* / *zesty*, and *kind* / *caring* / *generous* (at extremes of D2 and D1 respectively), come intermediate words such as *jovial*, sharing aspects of both.

These polarities seem plausible as the kind of distinctions one might make between different extremes of product image. For example, it is possible to interpret the advertising of a range of products as diverse as whiskey/cola ready-mixed drinks, Swedish-made cars, and men's suits, as the advertisers' attempt to situate these products in different regions of Figure 1.

Figure 1(a). Three-dimensional spatial model for 88 product-descriptive adjectives: D1-D2 plane

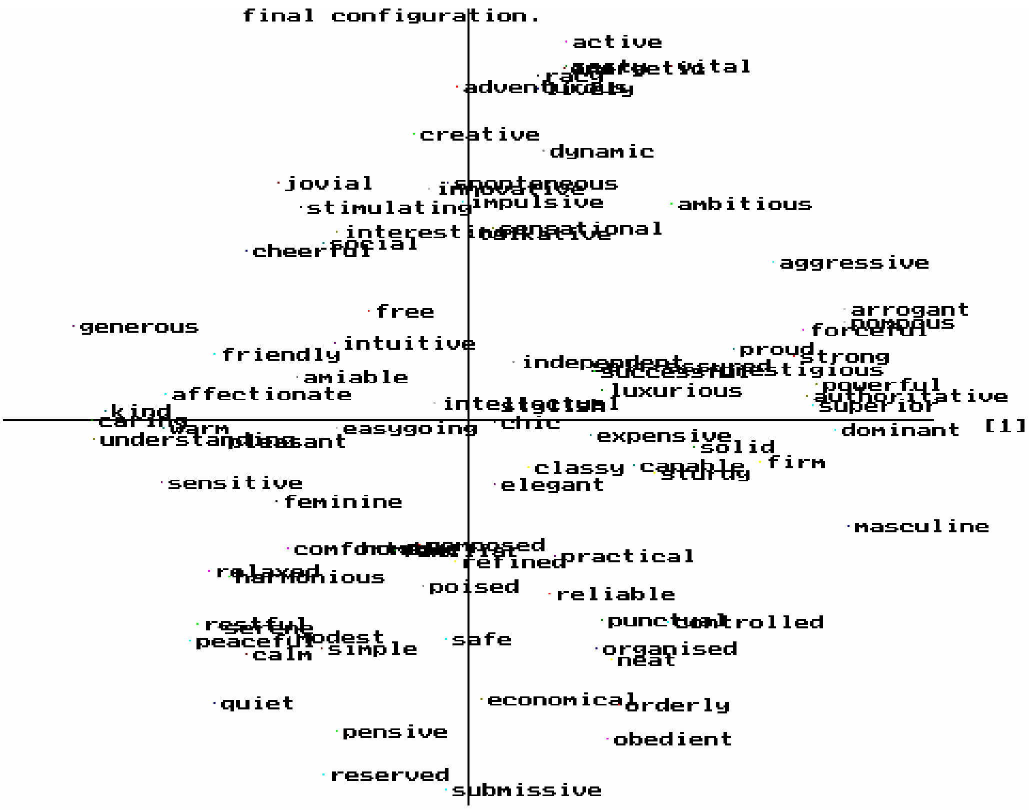


Figure 1 (b). Three-dimensional spatial model for 88 product-descriptive adjectives: D1-D3 plane

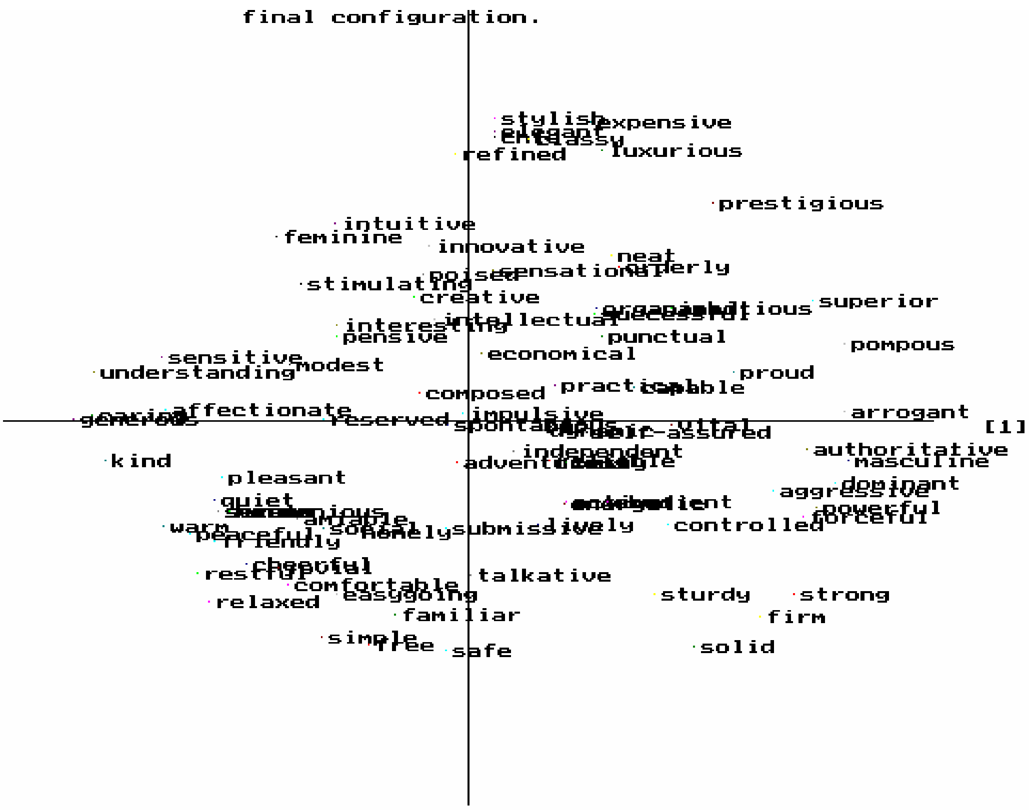
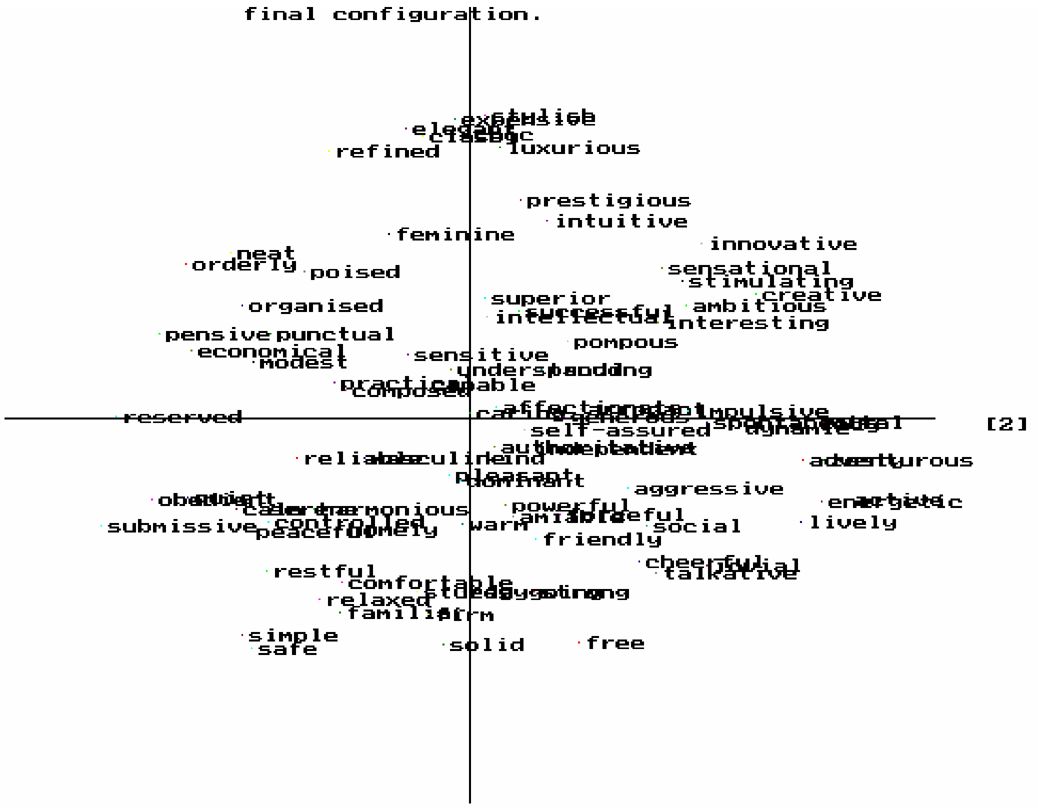


Figure 1(c). Three-dimensional spatial model for 88 product-descriptive adjectives: D2-D3 plane



The co-occurrences from the current data, processed with MDS, yielded a three-dimensional spatial model in which descriptors were arranged in four tight clusters at the corners of a tetrahedron. Empty voids separated these clusters, and within each cluster, distinctions between the descriptors were obscured. Applying Homogeneity Analysis (available in the SPSS package as HOMALS) had the same result.

If our lexicon for product images were indeed reducible to four separate lists of synonymous terms, it would provide little scope for expressing the diverse way in which images differ; the vast majority of the terms (and of the English language!) would be redundant. Indeed, the descriptors in this study were specifically chosen to include nuances of intermediate meaning, to provide a fine-meshed sampling of 'semantic space'. We believe the clumping to be an artefact. Other sorting studies in the literature report the same phenomenon. Slooff and van der Kloot (1985), using HOMALS for their analysis, found it necessary to remove six adjectives from their item set, since their inclusion in the sorting data caused the spatial model to degenerate into two clumps. Even then their model basically consisted of three clumps arranged in a triangle. For another comparison from outside market research, Boster (1986) collected sorting data for *colours*, using a procedure of repeated partitioning. The model derived from the co-occurrences is again degenerate, with all the colours in two clusters, and not the continuous 'colour wheel' one would expect.

Two serious but unavoidable obstacles to viewing and understanding this model are its three-dimensionality, and the profusion of descriptors. The full potential of Figure 1 requires an enlarged version, preferably inspected with a suitable computer interface allowing it to be rotated or viewed with a stereoscope.

The tree model (Figure 2) is clearer. It brings together clusters of related adjectives, which emerge, from the data. One can see, for example, that *firm*, *solid*, *masculine*, *powerful*, *strong* are closely associated, as are *affectionate*, *generous*, *warm*, *caring*, *kind*, *sensitive*, *understanding*. In the course of traversing links in Figure 2 to get from one adjective to another, the farther to the left one goes, the greater the distance between them and the less similar they are in meaning, according to the model. The joining of branches toward the left of the tree indicates how these clusters are related. Subdivision of branches toward the right indicates the further distinctions within them.

However, tree models have the limitation that they cannot express the extent to which an intermediate descriptor shares aspects with two clusters, or whether a gradient along some underlying dimension is responsible for the distinctions within clusters. Looking at the members of any of the clusters, for instance *jovial*, *cheerful*, *amiable*, they are all equally close to a member of a different cluster, for instance *kind*. In general, a tree is complementary to a spatial model, highlighting different aspects of the structure, and neither model on its own is capable of showing all the structure contained in the data.

Discussion

This study has explored the semantic structure of an 88-adjective lexicon or ‘concourse’ designed for discussing product images. The results were models of this product-image concourse, in the form of a three-dimensional ‘semantic space’ and a tree diagram.

The concourse is intended to be general enough to encompass the image of quite different categories of products, such as alcoholic spirits, cars, wallpaper, and so on. Thus mapping the lexicon for each category should not be necessary. Depending on the application, the decision whether the words are good or bad descriptions will require using them in a more or less metaphorical way. A car, for instance, can be classified with relative ease as *arrogant* or *amiable*, *racy* or *reserved*, *luxurious* or *simple*... similar decisions about a wallpaper pattern might be less straightforward. But “... a TORNADO cannot be either *fair* or *unfair* to any degree, [...] yet our subjects consistently rate TORNADO as *very unfair*!” (Osgood 1971). At any rate, words which informants find too foreign in a given context to use as descriptors at all can simply be omitted from the lexicon – which is one reason for making it so large in the first place.

These models are not ends in themselves, however. Their value lies in their potential use as nets for capturing the abstract images of products. One way of doing this is to represent the “market position” of a product within the spatial model as a point x_p, i.e. the ideal point model mentioned in the Introduction. Such applications would require more dissimilarity data, but this time relating to the dissimilarities between the product and individual descriptors. One might ask informants to rate the applicability of each descriptor in turn to the specific brand, perhaps on a binary scale (“Do you associate this word with the product, or not?”), or on a finer-grained scale of applicability, say 1 to 7. If the ideal point model is valid, these measures of association should correlate well with the distances d_{ip} between x_p and the points x_i corresponding to the descriptors. Highly-applicable adjectives should form a “cloud” in the spatial model so that locating x_p is a matter of specifying its centre.

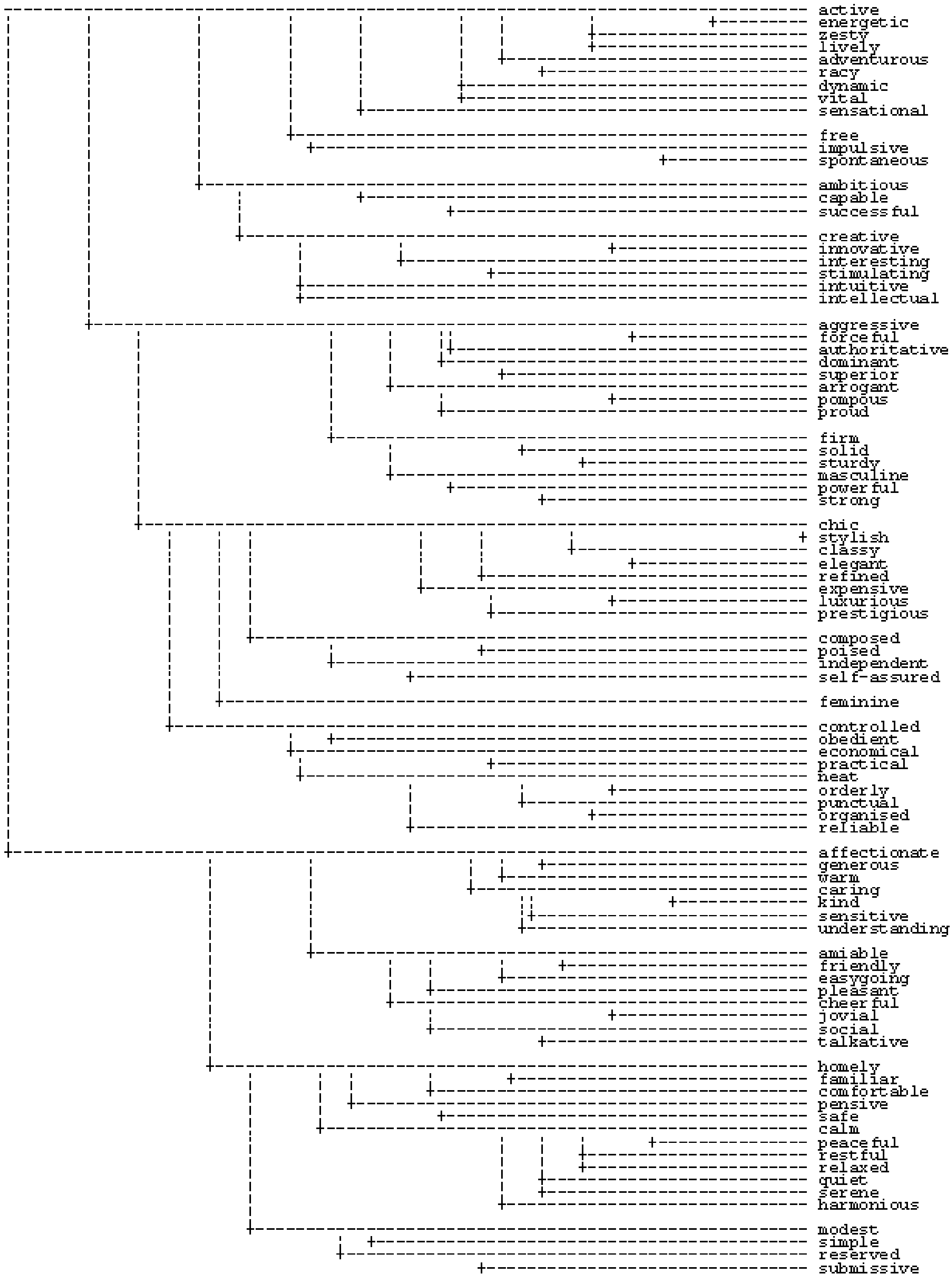


Figure 2. Hierarchical tree model for 88 product-descriptive adjectives, showing clusters of related concepts.

Alternative models of descriptor/product associations exist: several are discussed in Coxon (1999). People's responses to products are subjective, whereas their GPA-sorting responses are objective, and the common element of these models is that they provide ways to integrate these two forms of data. Until we have applied Figures 1 and 2 in this way, to investigate the images of actual products, these remarks remain speculative. However, the tools are available for the use of other researchers. If their applications involve more specialised concourses to be mapped, we have also described suitable procedures for collecting and analysing data.

The size of the lexicon in this case restricted us to the Method of Sorting as the only practical procedure for collecting data. A variant of this procedure was used in which the adjectives were divided into smaller randomised sub-sets or 'split decks', which participants sorted into groups, on the basis of the similarities between them. The instructions ensured that each participant provided a whole sequence of such groupings. But we must mention in passing the limitations of the sorting procedure. Inevitably, participants sort the items into different arrangements, with different demarcations between the groups. The split decks increase such variations by ensuring that each participant's decisions are made in a different context. Nevertheless, we assume that there is a "true" structure of inter-item similarities, a "true" semantic structure to the meanings of the adjectives, and that the participants' deviations (their lack of unanimity) are random ones. Thus there is an element of uncertainty to any model reconstructed from such unavoidably noisy data. The extent of uncertainty is unknown (MDS does not offer the significance tests which we have come to expect from statistical methods), so specific details of Figures 1 and 2 must be interpreted with caution.

A limitation of this kind of semantic approach to a lexicon is that the meaning of words is context-dependent. Variations in the item set can affect the final structure by calling the attention of informants to different meanings of the descriptors, and different distinctions among them. Fourteen of the 88 adjectives used in this study demonstrate this, since they also appear in Goldberg's (1992) markers of the Big-5 personality structure. These are *talkative*, *energetic*; *quiet*, *reserved*; *kind*, *warm*; *practical*, *neat*, *organised*; *calm*, *relaxed*; *creative*, *intellectual*; *simple*. In Figures 1 and 2 these items are not always grouped together in the same way as in the Big-5 theory. *Energetic* and *talkative*, which serve in the Big-5 theory as markers of the personality 'pole' labelled Factor I+ (Extraversion), are divided in Figure 2 between an *active* / *lively* and an *amiable* / *friendly* / *social* cluster. *Quiet* and *reserved*, which are markers of Factor I- (Introversion), are again separated, *quiet* appearing with *calm* and *relaxed* in one cluster, while *reserved* clusters with *modest*, *simple*, *submissive*. Indeed, *simple* was understood in the context of the words used in the Goldberg study, with a different sense from the interpretation placed on it here. This pitfall must be watched for in any application of MDS.

Of course, the same MDS techniques can also be applied to dissimilarities between products (Bimler & Kirkland 1998). But this involves repeating the hard work, each time a new category or combination of products is considered. It also requires more interpretative skill, since identifying each dimension of the semantic space requires inspection of the category examples at each extreme of the axis, while speculating about the attributes which distinguish them. For product comparisons, the dimensions are not self-labelling, as in this study.

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Acknowledgements

Our volunteer participants generously provided the data reported here and Dick Brunton assisted with adjective selection. We are indebted to the Editor of the Marketing Bulletin and to two anonymous reviewers, whose constructive commentary on earlier versions of this paper helped greatly to increase its coherence.

David Bimler is an independent researcher, and John Kirkland is an Associate Professor in the Department of Educational Studies and Community Support, Massey University.